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Original article

ECG analysis using wavelet transform: application to myocardial ischemia detection

Détection des événements ischémiques myocardiques à partir de la transformée en ondelettes du signal ECG

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Abstract

In this paper, we propose a method for the detection of myocardial ischemic events from electrocardiogram (ECG) signal using the wavelet transform technique. The wavelet transform is obtained using the quadratic spline wavelet. Then, based on the wavelet transform values, the characteristic points of the ECG signal are found out. These characteristic points are used to identify any ischemic episodes present in the ECG signal. This technique can be extended for other types of cardiac abnormality detections, which induce changes in the ECG.

Résumé

La transformée en ondelettes est obtenue en utilisant l'ondelette de spline quadratique. En se basant sur les valeurs de la transformée en ondelettes, les points caractéristiques du signal d'électrocardigramme (ECG) sont détectés. Ces points caractéristiques sont employés pour identifier tous les épisodes ischémiques présents dans le signal ECG. Cette technique peut être étendue à la détection d'autres types d'anomalies cardiaques, qui se traduits par des modifications de l'ECG.

Keywords: ECG; Myocardial ischemia; Wavelet transform

Mots clés : ECG ; Ischémie cardiaque ; Transformée en ondelettes

1. Introduction

The object of automation of electrocardiogram (ECG) analysis is to reduce the time required for human interpretation and analysis of ECG recordings from the Holter monitoring equipment. It is a subject of major theoretical and practical interest. It can also be used for online analysis.

In Holter monitoring, the ECG signals from the patient under observation are digitized, compressed and stored in a hard storage device. This data are later uncompressed and analyzed by the cardiologists to detect abnormalities (normally, 24 h data are taken). The analysis of this data takes a substantial time and the automation of the analysis would be a promising one.

Some of the existing techniques use a series of band-pass filters to extract the *QRS* complexes from the ECG signal, which under severe baseline drift and other high frequency noises, fails to detect the characteristic points to an acceptable accuracy. Some use neural network based adaptive identification algorithms [9], which can be used for only a particular type of pattern. The wavelet transform based technique can be used to identify the characteristic points of

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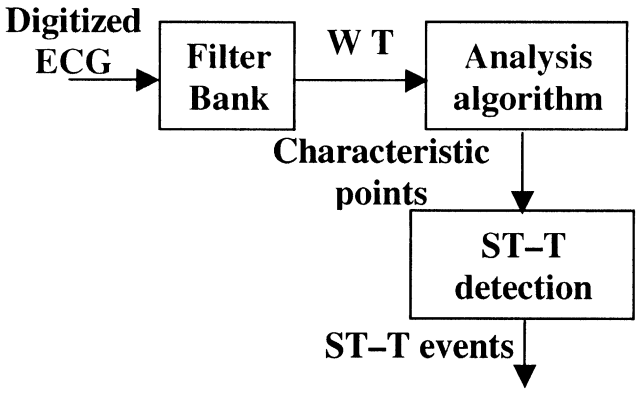

Fig. 1. Block diagram of the entire process.

the ECG signal to a fairly good accuracy, even with the presence of severe high frequency and low frequency noises [8,10,11]. Our aim here is to describe an elegant algorithm, which uses WT to identify the characteristic points of the ECG signal, and hence to identify the myocardial ischemic episodes.

2. Methods

As an alternative to the normal filtering techniques, which use different narrow-band filters to extract the frequency contents of the signal, the wavelet transform technique can be used. In wavelet transform technique, the signal is analyzed at different frequencies with different resolutions. It is called multiresolution analysis (MRA) (Fig. 1).

The wavelet used in this work is the quadratic spline wavelet [12]. The reasons for choosing this particular wavelet for the analysis purpose are as follows:

- It has a very compact support,
- It has a generalized linear phase, so there is a determinate relationship between ECG characteristic points and the modulus maxima, or the zero-crossing points of the WTs.

The Fourier transform (FT) of the quadratic spline wavelet is given as:

$$\hat{\Psi}(\omega) = i\omega\left(\frac{\sin\frac{\omega}{4}}{\frac{\omega}{4}}\right)^4$$

The FIR filter coefficients that make up the decomposition and reconstruction filter banks and the Lipschitz coefficients for the decomposition algorithm are given in Tables 1 and 2.

There is a relation between the characteristic points of the signal and those of their WT at different levels [3,4,13]. For example, for the wave in Fig. 2, the wavelet transform at scale 2^1 is given. The wave's rising edge corresponds to a negative minima and the dropping edge corresponds to a positive maxima. The moduli of these maxima or minima corresponding to the same edge are named as the modulus maxima line. If the uniphase wave is symmetric to its peak, then its peak corresponds to the zero-crossing point of the

Table 1
FIR filter coefficients for quadratic spline wavelet

N	*H*	*G*	*K*	*L*
–3			0.0078125	0.0078125
–2			0.054685	0.046875
–1	0.125		0.171875	0.1171875
0	0.375	–2.0	–0.171875	0.65625
1	0.375	2.0	–0.054685	0.1171875
2	0.125		–0.0078125	0.046875
3				0.0078125

G, decomposition high pass filter coefficients; *H*, decomposition low pass filter coefficients; *K*, reconstruction high pass filter coefficients; *L*, reconstruction low pass filter coefficients.

positive maxima-negative minima pair with a delay of exactly $2^{j-1} - 1$ points, where *j* represents the scale.

After obtaining the wavelet transform coefficients at different scales, the next step is to find out the ECG characteristic points from these coefficients. The characteristic points of the ECG waveform are shown in Fig. 3.

2.1. R-peak detection

For detecting the *R*-peak, the modulus maxima–minima pair is located for the lowest scale (2^1), which is done by fixing a threshold for detection. After this, the maxima–minima pairs for other scales are located within the neighborhood of these maxima–minima pairs. If the amplitudes of the maxima–minima pairs are consistent compared to that at the lower scale, or it is increasing, then the corresponding modulus maxima–minima pair is treated as one that corresponds to a true *R*-peak. This method reduces the effect of low frequency artifacts and also the high frequency non-morphological noise.

Table 2
Normalization coefficients λ_j for the quadratic spline wavelet

j	λ_j
1	1.5
2	1.12
3	1.03
4	1.01
5	1.00

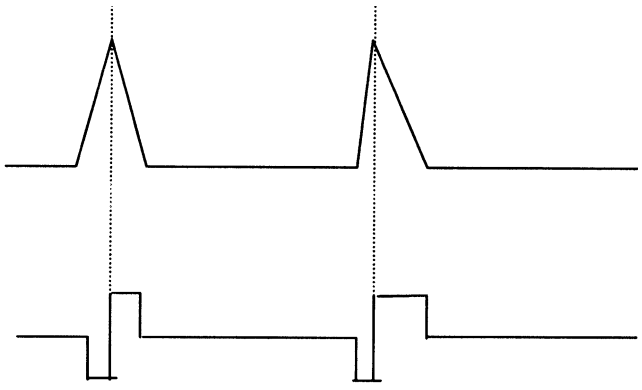

Fig. 2. The uniphase wave and its WT at scale 2^1.

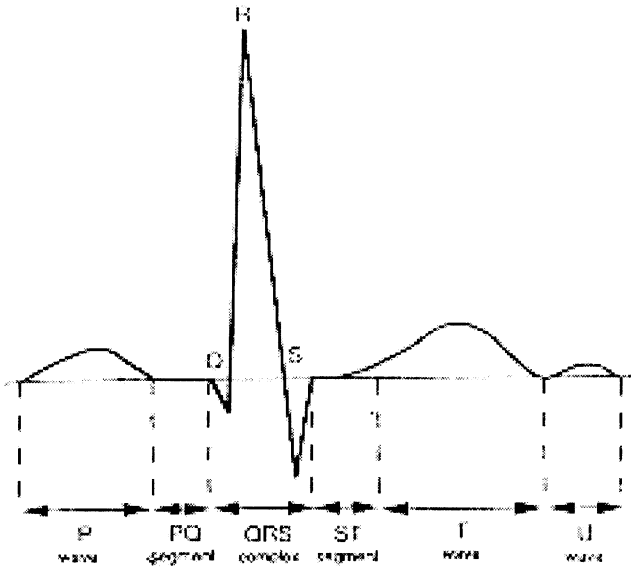

Fig. 3. ECG characteristic points.

2.2. QRS onset and offset detection

Generally, the *Q* and *S* waves are high frequency and low amplitude waves and their energies are mainly at small scale. So, the detection of these waves is done with WT at low scale. From the modulus maximum pair of the *R*-wave, the beginning and ending of the first modulus maxima before and after the modulus maximum pair are detected within a time window. These correspond to *QRS* onset and offset points.

2.3. T and P wave detection

T and *P* waves are normally low frequency waves, so WT at high scale is used to locate these waves. In this work, WT up to four scales are taken and the scale 2^4 is used to locate *T*- and *P*-waves.

The *T*-wave creates a pair of modulus maxima with a different sign on $W_{2^j}f(n)$ at scale 2^4, within a time window after the detected *R*-peak. Since the wave is almost symmetric to its peak, the peak of *T*-wave corresponds to the zero-crossing point of the modulus maximum pair with a delay of 2^{4-1}–1 (7) points.

The peak, onset and offset of the *P*-wave are detected in a manner similar to those of the *T*-wave within a time window before the detected *R*-wave.

2.4. Detection of MI from the ECG characteristic point

Different ECG changes related to the evolution of ischemia have been described [2], including *T*-wave amplitude changes, *ST* deviations and even alterations in the terminal portion of the *QRS* complex. The use of global representations for the *ST–T* complex instead of a single point from the *ST* segment better characterizes ischemia patterns [5,7] and yield better identification of occluded artery.

The most important ECG change associated with ischemia is the *ST* segment elevation or depression, with depression being most common. Also, this can be along with *T*-wave amplitude changes or even *T*-wave inversion. So ischemia can be detected using these two measurements. For finding the *ST* depression level, a reference level is found out first. This is done by drawing a line between two or more *P*-waves where they return to the base line (or starting of *P*-wave). From the characteristic point detection algorithm, we obtain the *P*-wave onset and offset of all the cardiac cycles. *ST*-segment is the segment of ECG between *QRS* offset and *T*-wave onset. The deviation of this segment from the reference line is found out. The amplitude of *T*-wave is also found by measuring the distance of the *T*-peak from the reference line. Having obtained these two values, we can come to a conclusion as to whether the cardiac cycle contains an ischemic episode or not.

Table 3
Comparison of performance measures

Method	ST_{se} (%)	$ST + P$ (%)
RMS method [7]	85	86
Taddei et al. [1]	84	81
Magaveras et al. [9]	89	78
Jager et al. [5]	87	88
This method	92	86

3. Results

To demonstrate the effectiveness of this technique, the digitized ECG data were taken from the European *ST–T* database and a performance evaluation was carried out using a method developed for the *ST–T* change detection algorithm [6].

The European *ST–T* change database [14] consists of the recordings of 90 double channel 2-h ECG signal with a sampling rate of 250 s^{-1}, which contain *ST–T* complex episodes annotated on an individual lead basis by cardiologists. The amplitude scale is 5 uv/point.

The performance evaluation method for *ST–T* change detection algorithm [6] consists of calculating certain performance indices, which are; *ST* sensitivity (ST_{se}), which is an estimate of the likelihood of detecting an ischemic *ST* episode; *ST* positive predictivity ($ST + P$), which is an estimate of the likelihood that a detection is a true ischemic *ST* episode; ischemic sensitivity (IS_{se}), which is a fraction of true ischemia, which is detected; ischemic positive predictivity ($IS + P$), which is the fraction of detector annotated ischemia, which is true ischemia.

The above performance measures were calculated for the algorithm proposed here. The comparison of the performance measures with some other algorithms, which are used to find ischemia, is given in Table 3.

The ischemic sensitivity and ischemic positive predictivity were calculated as 87.5% and 93.3%, respectively.

Another method for the comparison of the algorithm is the plot of the *ST* change amplitude values, measured by the algorithm against the values given by the annotation files. Using the scatter plot, a linear regression line is fitted. The

Table 4
Comparison of correlation coefficients

Method	Regression line equation	Correlation coefficient
RMS [7]	$Y = 4.33\,X - 10.72$	0.963
This method	$Y = 1.021\,X - 14.48$	0.971

correlation coefficient and the mean error are found and compared (Table 4). The plot is given in Fig. 4.

4. Conclusion

From the result, it can be seen that this method is having a comparatively higher sensitivity and nominal positive predictivity value. The algorithm treats each beat individually, hence the accuracy in measurement. The correlation coefficient is closer to unity compared to that of the RMS method [7], suggesting more closeness of the measurements to the true value. The limitation of this method is that the computations required are higher than those required by other methods. This is mainlydue to the calculation of WT. But the added advantage over other methods is that this can be easily extended to detect other abnormalities of the ECG signal.

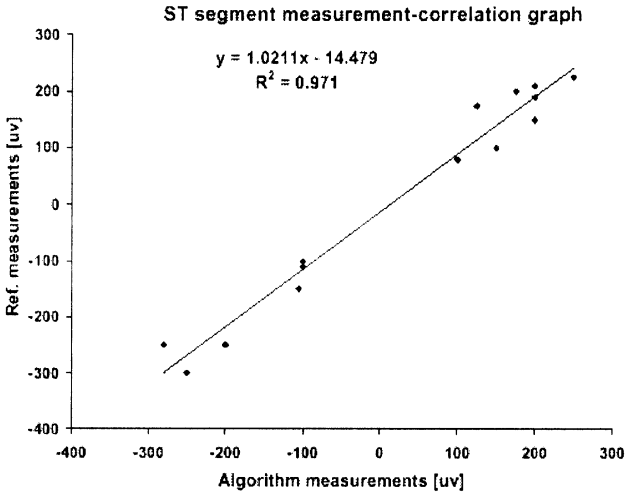

Fig. 4. Measurement–correlation graph.

References

[1] Taddei A, Constantino G, Silip R, Emdin M, Marchesi C. A system for the detection of ischemic episodes in ambulatory ECG. Computers in Cardiology. Los Alamitos, CA: IEEE Computer Society Press; 1995. p. 705–8.

[2] Cohn PF. Silent Myocardial Ischemia and Infarction, 8–18. New York: Marcel Dekker; 1993. p. 87–97.

[3] Li C, Zheng C, Tai C. Detection of ECG characteristic points using wavelet transform. IEEE Trans Biomed Eng 1995;42(1):21–8.

[4] Golden Jr DP, Wolthuis RA, Hoffler GW. A spectral analysis of the normal resting electrocardiogram. IEEE Trans Biomed Eng 1973; 20(5):366–72.

[5] Jager F, Moody GB, Mark RG. Detection of transient ST segment episodes during ambulatory ECG monitoring. Comput Biomed Res 1998;31(5):305–22.

[6] Jager F, Moody GB, Taddei A, Mark RG. Performance measures for algorithms to detect transient ischemic ST segment changes. Computers in Cardiology. Los Alamitos, CA: IEEE Computer Society Press; 1991. p. 372–96.

[7] Garcia J, Sornmo L, Olmos S, Laguna P. Automatic detection of ST–T complex changes on the ECG using filtered RMS difference series: application to ambulatory ischemia monitoring. IEEE Trans Biomed Eng 2000;47(9):1195–201.

[8] Vetterly M, Kovacevic J. Wavelet and Subband Coding. first ed. Upper Saddle River, NJ: Prentice Hall; 1995.

[9] Magaveras N, Stamkopoulos T, Pappas C, Strintzis MG. An adaptive backpropagation neural network for real-time ischemia episodes detection: development and performance analysis using the European ST–T database. IEEE Trans Biomed Eng 1998;45:805–13.

[10] Raghuveer MR, Bopardikar S. Wavelet Transforms: Introduction to Theory and Applications. second ed. Boston, MA: Addison Wesley; 1996.

[11] Special issue on wavelets. Proc IEEE 1996;84(4).

[12] Mallat S, Zhong S. Characterization of signals from multiscale edges. IEEE Trans PAMI 1992;14(7).

[13] Mallat S. Zero crossing of a wavelet transform. IEEE Trans Inf Theory 1991;37(4).

[14] European ST–T change database. http://www.physionet.org/.